

# From Zero to R

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11/02/2020

# Summary

- What is R
- What can I do with R
- Working with R in Rstudio
- R basic characteristics
- Visualizing data with ggplot
- Data carpentry
- Writing Functions

## Section 1

# Introduction

# What is R

*R is a **free software environment** for statistical computing and graphics, available at <https://cran.r-project.org/>*

- **open source** → huge community
- **statistical computing** → data mining/analysis
- **graphics** → data mining/visualization
- **programming** → language (command-line interpreter)

# Why R

## Pros

- ① It's free!
- ② Almost everything is ready
- ③ It easy to find “how to”s on the web

## Cons

- ① Bugs errors and inconsistencies
- ② It is not a true programming language
- ③ not always user friendly

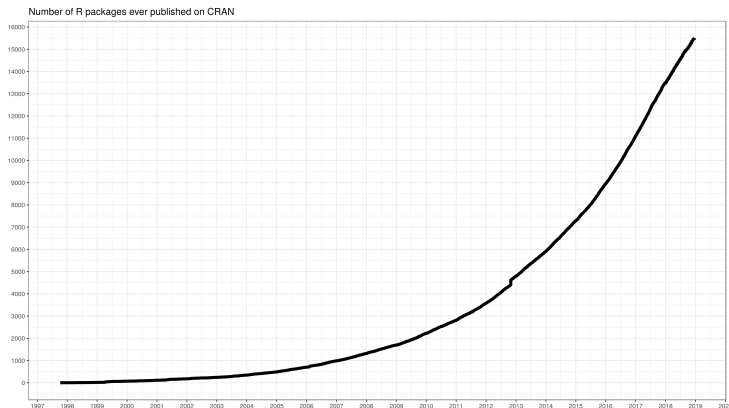
# R Packages

- New functionalities are added to R by using **packages**.
- A package is a set of **documented** functions to solve specific tasks

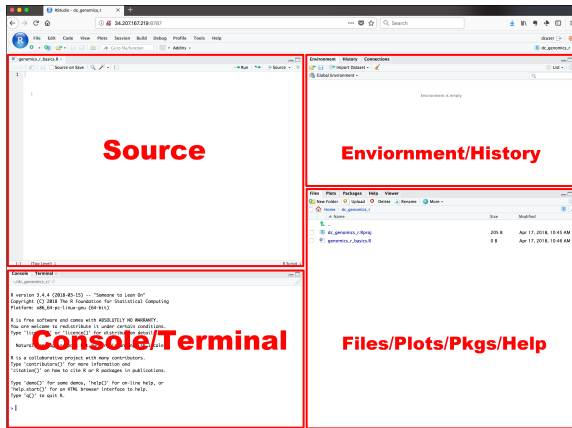
## Package sources

- CRAN - <https://cran.r-project.org/>
- Bioconductor - <https://www.bioconductor.org/>
- GitHub - <https://github.com/>

# Packages on CRAN



# RStudio





# RStudio



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# How do we work

## Organize your work

- Keep track of what you do in the text editor
- Execute the commands in the console
- **Save** your code for next time ;-)

## Store your scripts

- **.R** files with this extension can be executed by R. The comments are marked by #
- **.Rmd** these files are typical of RStudio and consist of a mixture of text and code *chunks*



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# Key idea #1: Working directory

Is your reference directory

- reading files (data or code)
- writing files
- saving objects

```
## this function gets the working directory  
getwd()
```

## Key idea #2: Workspace

Is the place (in memory) where R stores all the stuff you can use for the analysis.

- functions
- variables
- saving objects

R will “see” only things that are in the workspace!

# Populating the workspace

To put something in the workspace one uses either the “->” or “=”

```
## this line of code creates a place called "a"  
## in the workspace, filling it with the number 3
```

```
a <- 3
```

The content will show up in the “Environment” tab of Rstudio ...

## Section 2

### R basics in a nutshell

# Basic data Types

R can understand several basic **data types**

- Numeric: number with the comma
- Integer: number without comma
- (Complex number)
- Logical: TRUE/FALSE
- Character: a sequence of characters, everything between " "



## Assignment

```
## create a set of basic objects  
## operate on them with basic operations (+,-,*,/)  
## to create character vectors use " ".
```

```
a <- 1
```

```
b <- 2
```

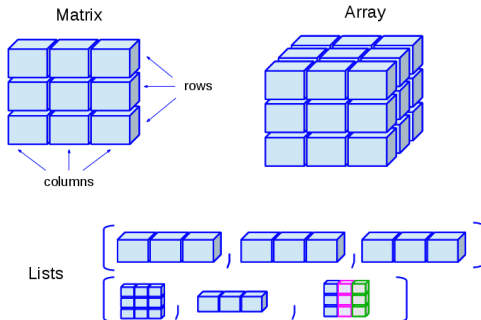
```
c <- a+b
```

### Question time

- can you combine object of different type?
- what does it happen if you sum two logical variables?
- is 1 different from "1"?

# Multidimensional Objects

Multidimensional objects are constructed by collecting together multiple basic data types



# Functions

Functions can be seen as “digestors”, which handle some input producing output.

*## a name followed by parenthesis is a function ...*

```
pippo()
```

Inside the parenthesis you have **arguments** which determine the behavior of a function

*## what does this do?*

```
d <- sqrt(9)
```

*## and this?*

```
p <- seq(from = 1, to = 5, by = 2)
```

## Getting Help

The possible arguments of a function can be checked in the extensive and complete R help

```
## shows the help for the seq function  
?seq
```

# Functions and multidimensional objects

**Multidimensional objects** are created by specific **functions**, with really evocative names ;-)

```
## create
myvector <- c(1,2,3,4)
mymatrix <- matrix(seq(1,9), ncol = 3)
mydataframe <- data.frame("col1" = 1:3,
                           "col2" = c("one", "two", "three"))
mylist <- list("hey" = seq(1:30), "today" = "monday")

## show
mymatrix
```

```
##      [,1] [,2] [,3]
## [1,]    1    4    7
## [2,]    2    5    8
## [3,]    3    6    9
mydataframe
```

```
##   col1 col2
## 1    1  one
## 2    2  two
## 3    3 three
```

# Factors

Factors are character vectors with a limited number of values. For parsimony they are saved as numbers ...

```
myfactor <- factor(rep(c("treated","ctrl"), each = 3))  
myfactor
```

```
## [1] treated treated treated ctrl      ctrl      ctrl  
## Levels: ctrl treated
```

**Important** if not specified the levels of the factor are ordered in alphabetical order. The importance of this aspect will be clear when we will start dealing with plots

# Accessing Multidimensional Objects

- by **position**, giving the “coordinates”
- by **name** (more robust)

# Arrays, matrices and data frames

```
# like coordinates ...
mydataframe[1,]  ## first row
mydataframe[,1]  ## first column
mydataframe[, "col1"] ## the column "col1"

# slicing
mydataframe[1:4,1] ## the first four rows of the first column

# for data frames, the '$' symbol
# can be used to access the columns in a faster way
mydataframe$col1
```



# Lists

Lists are substantially unidimensional so we need only one index or one name

```
## here we need double brackets to get the element
```

```
mylist[[1]] # the first element
```

```
mylist[1:3] # from the first to the third element
```

```
mylist[["pippo"]] # the element named pippo
```

```
mylist$pippo # also here the element named pippo
```

## Assignment #2

```
# 1. create a dataframe with two columns,  
# one with the short name of each month,  
# the second with the number of days, the third with the (approx  
# 2. extract the season and transform it into a factor  
# 3. do the same with a list
```

```
data.frame()  
factor()  
list()
```

# Packages

The functionalities of R are expanded by “packages”. Packages contain functions and, optionally data. To make a package available you have to

- download and compile it on your machine
- load it in the workspace

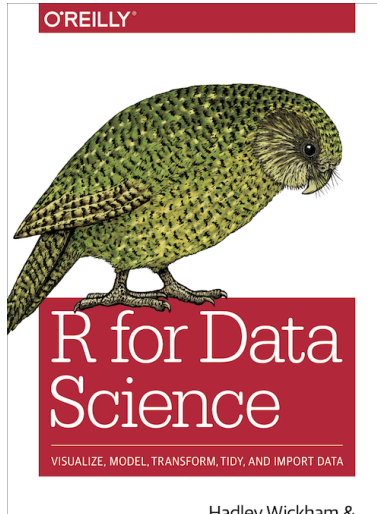
```
# install the package from CRAN on my machine  
install.packages("tidyverse")  
  
# makes the tools present in the package available on my workspace  
library(tidyverse)  
  
# load the mpg dataset in my workspace, otherwise I will not be able to use it!  
data(mpg)
```

## Section 3

# Wrangling data tables

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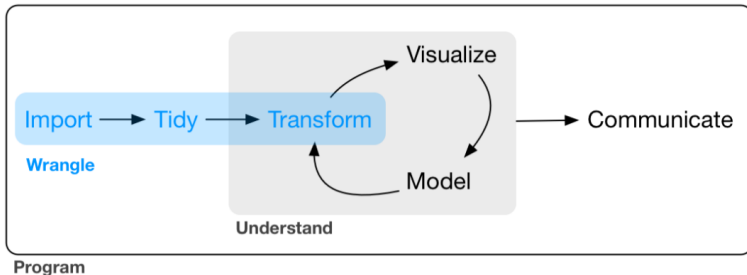
# My first Data visualization task



Pietro Franceschi

Hadley Wickham &  
John Fox  
From Zero to R

# Mind Map of data wrangling



# Tabular and tidy data

country	year	cases	population
Afghanistan	1999	1845	15467071
Afghanistan	2000	2666	20095360
Brazil	1999	31737	172006362
Brazil	2000	81488	174004898
China	1999	211258	1272015272
China	2000	211766	1280008583

variables

country	year	cases	population
Afghanistan	1999	1845	15467071
Afghanistan	2000	2666	20095360
Brazil	1999	31737	172006362
Brazil	2000	81488	174004898
China	1999	211258	1272015272
China	2000	211766	1280008583

observations

country	year	cases	population
Afghanistan	1999	1845	15467071
Afghanistan	2000	2666	20095360
Brazil	1999	31737	172006362
Brazil	2000	81488	174004898
China	1999	211258	1272015272
China	2000	211766	1280008583

values

we can think of them as enormous and complicated excel tables

## mpg dataset

This dataset contains a subset of the fuel economy data that the EPA makes available on <http://fuelconomy.gov>. It contains only models which had a new release every year between 1999 and 2008 - this was used as a proxy for the popularity of the car.

```
## load the library
library(tidyverse)
## load the data
data(mpg)
## show their header, first 5 lines
head(mpg,5)
```

```
## # A tibble: 5 x 11
##   manufacturer model displ  year   cyl trans      drv    cty   hwy fl    class
##   <chr>         <chr> <dbl> <int> <int> <chr>    <chr> <int> <int> <chr> <chr>
## 1 audi         a4      1.8  1999     4 auto(l5) f        18    29 p    compa-
## 2 audi         a4      1.8  1999     4 manual(m5) f        21    29 p    compa-
## 3 audi         a4      2    2008     4 manual(m6) f        20    31 p    compa-
## 4 audi         a4      2    2008     4 auto(av) f        21    30 p    compa-
## 5 audi         a4      2.8  1999     6 auto(l5) f        16    26 p    compa-
```

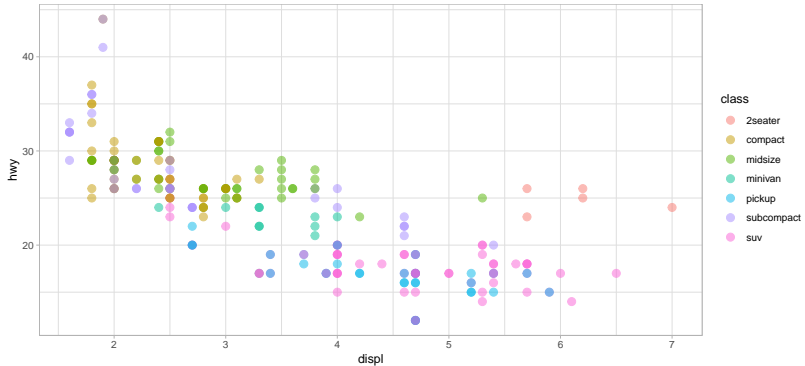


# Fast summary of my data

```
## this function gives a convenient summary of the data  
summary(mpg)
```

```
## manufacturer      model      displ      year  
## Length:234        Length:234    Min.   :1.600   Min.   :1999  
## Class :character   Class :character 1st Qu.:2.400   1st Qu.:1999  
## Mode  :character   Mode  :character Median :3.300   Median :2004  
##                                     Mean  :3.472   Mean  :2004  
##                                     3rd Qu.:4.600   3rd Qu.:2008  
##                                     Max.   :7.000   Max.   :2008  
##      cyl      trans      drv      cty  
## Min.   :4.000   Length:234    Length:234    Min.   : 9.00  
## 1st Qu.:4.000   Class :character Class :character 1st Qu.:14.00  
## Median :6.000   Mode  :character Mode  :character Median :17.00  
## Mean    :5.889                                     Mean  :16.86  
## 3rd Qu.:8.000                                     3rd Qu.:19.00  
## Max.    :8.000                                     Max.   :35.00  
##      hwy      fl      class  
## Min.   :12.00   Length:234    Length:234  
## 1st Qu.:18.00   Class :character Class :character  
## Median :24.00   Mode  :character Mode  :character  
## Mean    :23.44  
## 3rd Qu.:27.00  
## Max.    :44.00
```

# A plot!



# How we did it ..

```
ggplot(data = mpg) +  
  geom_point(mapping = aes(x = displ, y = hwy, col = class),  
              size = 3,  
              alpha = 0.5) +  
  theme_light() +  
  theme(aspect.ratio = 0.5)
```

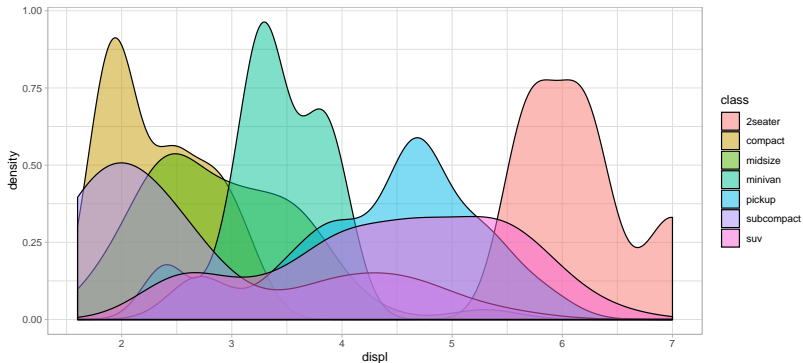
**Note** Here the functions are linked by `+`, this way of writing has been used to introduce a so called “grammar” of graphics

# Dissecting the command

```
## create an empty canvas ready for mpg  
ggplot(data = mpg) +  
  ## on the canvas plot points linking their aesthetics to the column names  
  geom_point(mapping = aes(x = displ, y = hwy, col = class),  
              size = 3,  
              alpha = 0.5) +  
  ## add additional general aesthetics  
  theme_light() + ## simple colors  
  theme(aspect.ratio = 0.5) ## plot aspect ratio
```

- `ggplot()` - create the plot area
- `geom_something()` - add graphic elements to the plot
- `aes()` function to map graphical properties to columns in the data

## Now a density plot!



# On ggplotting

- manipulate “global” properties outside `aes()`
- link them with column inside `aes()`
- find the required and optional aesthetics in the help (e.g. `?geom_point`)

## Mind the apex!

*## when you specify the names of the columns  
## pay attention to the apex!*

```
"ciao" # - string  
'ciao' # - string  
`ciao` # - the "name" of the column
```

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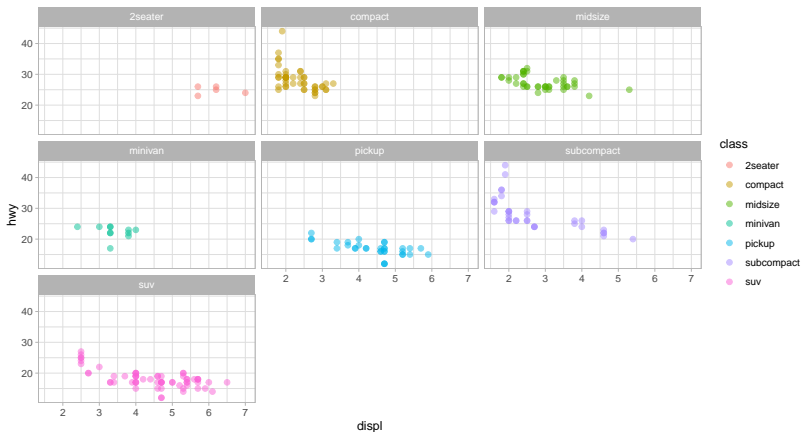
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## Assignment #3

- 1 Play around with mpg changing the type of plots
- 2 Associate aesthetics to categorical or continuous properties
- 3 Make a boxplot of “displ” as a function of the class of the vehicle
- 4 Just play and ask!



# Splitting the plot in subplots



## Here the trick

```
## group specific subplots
ggplot(data = mpg) +
  geom_point(mapping = aes(x = displ, y = hwy, col = class),
              alpha = 0.5, size = 2) +
  facet_wrap(~class) + ## !!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
  theme_light() +
  theme(aspect.ratio = 0.5)
```

*facet\_wrap() and facet\_grid() can be used to split the content of a plot according to one or more categorical variables*

Faceting can be also used with a clever trick to display multiple variables in the same multiplot . . .

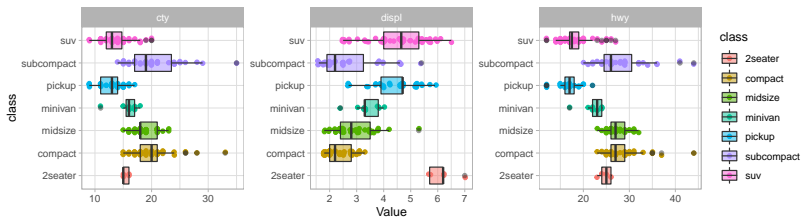
## Long and Wide data.frames

The same *tidy* data.frame can be organized in a **wide** and a **long** format. Typically we prefer to work with wide data, but long formats can be extremely handy . . .

country	year	cases
Afghanistan	1999	745
Afghanistan	2000	2666
Brazil	1999	37737
Brazil	2000	80488
China	1999	212258
China	2000	213766

country	1999	2000
Afghanistan	745	2666
Brazil	37737	80488
China	212258	213766

table4



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# Edgar Anderson's Iris Data

This famous (Fisher's or Anderson's) iris data set gives the measurements in centimeters of the variables sepal length and width and petal length and width, respectively, for 50 flowers from each of 3 species of iris.

The species are Iris **setosa**, **versicolor**, and **virginica**.

```
## you get it with  
data(iris)  
## visualize data  
head(iris,5)
```

##	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
## 1	5.1	3.5	1.4	0.2	setosa
## 2	4.9	3.0	1.4	0.2	setosa
## 3	4.7	3.2	1.3	0.2	setosa
## 4	4.6	3.1	1.5	0.2	setosa
## 5	5.0	3.6	1.4	0.2	setosa

# Assignment #4

- 1 Look for correlation between Sepal.Length and Sepal.Width (Petal.Length and Petal.Width) for the three iris varieties
- 2 Make a faceted boxplot showing the four iris properties as a function of the species

# Read and Write data

## Reading

- in RStudio directly import data tables with the *Import Dataset* command present in the Environment tab
- from the command line several read function are available
- to avoid strange behavior keep your files as simple (tidy!) as possible ... no colors, no merged cells, ...

## Writing

- the object in the environment can be saved in compressed .RData format
- tables can be written with `write.csv`, `write.table` (or `write_csv` and `write_table` from the `readr` package)
- the function from `readr` are more efficient and handle better the row names



## Example

```
## save obj1 and obj2 in the mydata.RData file ...  
save(obj1,obj2,file = "mydata.RData")
```

```
library(readr)  
## here the data are in a csv called "wines.csv"  
wines <- read_csv("data/wines.csv")  
  
head(wines,5)
```

```
## # A tibble: 5 x 14  
##   alcohol malic_acid ash ash_alkalinity magnesium tot._phenols flavonoids  
##   <dbl>    <dbl> <dbl>      <dbl>      <dbl>      <dbl>      <dbl>  
## 1    13.2      1.78  2.14      11.2      100      2.65      2.76  
## 2    13.2      2.36  2.67      18.6      101      2.8       3.24  
## 3    14.4      1.95  2.5       16.8      113      3.85      3.49  
## 4    13.2      2.59  2.87      21       118      2.8       2.69  
## 5    14.2      1.76  2.45      15.2      112      3.27      3.39  
## # ... with 7 more variables: non.flav._phenols <dbl>, proanth <dbl>,  
## #   col._int. <dbl>, col._hue <dbl>, OD_ratio <dbl>, proline <dbl>, class <chr>
```

List of Chemical properties of a group of three types of wines  
(Barolo, Barbera and Grignolino)

# Assignment #5

- 1 Get the wines data from GitHub (wines.csv)
- 2 Import the data into R
- 3 make a text summary of your data (`summary()`)
- 4 Plot the relation between proanthocyanidins and total phenols for the three types of wines.
- 5 Can you do a boxplot of the different properties of the wines (also here remember wide and narrow data.frames)?

## Section 4

# Data Carpentry

# Data Carpentry

*With the term “data carpentry” we identify all the set of operations/manipulations we currently do during the process of data exploration*

## Typical Operations

- Select some columns (variables)
- Select some rows
- Transform some of the columns (e.g. sum them ...)
- Calculate some statistics on a group of samples

## The old way ...

In the “standard” data analysis workflow, when several steps of transformation are needed the output of each transformation are saved and become the input of the subsequent step. This is time and memory inefficient ...

```
## suppose you want to make a sequence from 1 to the square root of 10  
a <- 10  
b <- sqrt(a)  
c <- seq(1,b,1)  
  
## we create intermediate ancillary objects
```

# Piping

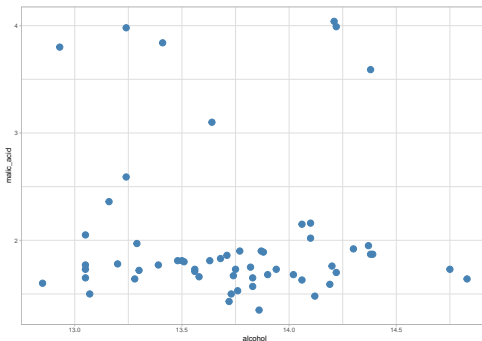
Better would be to “pipe” the output of a function to the input of another function ... no intermediate saving, but also a code easier to read ...

```
## pipe  
%>%
```

This is the “pipe” operator which is added to R when you use tidyverse (actually magritteR ...)

## Plumber at work ...

```
wines %>%  
  filter(class == "Barolo") %>%      ## get only the Barolos  
  ggplot() +                          ## the data comes from the pipe!  
  geom_point(mapping = aes(x = alcohol, y = malic_acid),  
              col = "steelblue", size = 4) +  
  theme_light()
```



# Pipes

- Very compact and clear writing
- I'm not creating permanent intermediate objects
- It follows my “psychological” logic ... I'm not changing the data, but only digesting them ...



## First carpenter tools

- `select()` Used to include, exclude columns. to exclude just put a `(-)` before the name.
- `filter()` Used to focus only a subset of the rows depending on a criterion
- `mutate()` Used to modify the content of a column or combine columns together

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## Assignment #6

- 1 Load the iris data
- 2 Calculate the ratios `sepal.width/sepal.length` and `petal.width/petal.length` (with **`mutate()`**!)
- 3 Plot the two ratios for all the iris variety
- 4 Save the modified table as `.csv`
- 5 Open it with Excel and see if you managed to save the new columns

**Important** Everything should be done with pipes! So only one command!

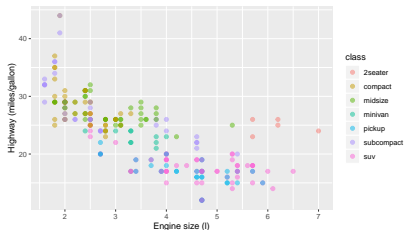
## Section 5

# Manipulating the graph aesthetics

## Axis labels and scales

As expected the axis labels in ggplot can be manipulated by “adding” functions to the ggplot chain

```
ggplot(data = mpg) +  
  geom_point(mapping = aes(x = displ, y = hwy, col = class),  
               alpha = 0.5, size = 2) +  
  ylab("Highway (miles/gallon)") + xlab("Engine size (l)")
```



```
# other additions xlim(...), ylim(...), scale_x_log10(...), scale_x_reverse(...)
```

## scale\_x\_continuous(...)

```
scale_x_continuous("Label",  
  limits = c(2, 6),  
  breaks = c(2, 4, 6),  
  label = c("two", "four", "six")  
)
```

*## Label of the axis  
## limits ... is a vector  
## where are the breaks?  
## custom names?*

# Themes

- The overall appearance of the graph can be highly customized, however some precooked solutions are already available within `ggplot`
- `ggplot` theme list
- A lower level control can be achieved by using the `theme(...)` function
- More themes are available within the `ggthemes` package

```
## just as a reminder  
install.packages("ggthemes")  
library(ggthemes)
```

## Plotting colors

A good choice of colors is fundamental to highlight the scientific message of every plot.

- We are not good in distinguishing too many different colors
- The level “visual” similarity of the colors will be implicitly perceived as sample similarity
- Do we need a B&W representation?
- Do we want to be “color blind” safe?



## Nice color schemas

In R colr names are specified as strings either by name or by hexadecimal color (`#e5f5f9`). An additional number between 0 and 99 can be added to the hexadecimal code to make the color transparent. Fr example, `#e34a33` is a type of **red**. `#e34a3350` is the same color, but half transparent.

- Color Brewer available in R in the package `RColorBrewer`
- `colortools` package. It allows the definition of specific color schemes starting from a chosen color.

## Setting the colors

```
## Setting manually the scale (discrete)
scale_color_manual(values=c("#999999", "#E69F00", "#56B4E9"), ## the colors
                    name = "myname") ## the name of the colorscale
scale_fill_manual(...)

## 'fill' and 'color' indicate what type of aesthetics is affected

scale_color_brewer(...)
scale_fill_brewer(...)
## make the brewer colorschemes directly available in ggplot
```

*## Setting manually the scale (continuous)*

```
scale_colour_gradient(low = "white",  
                      high = "black")
```

*##the same holds for fill*

```
scale_colour_gradient2(low = "red",  
                       mid = "white",  
                       high = "blue",  
                       midpoint = 0,  
                       name = "myscale")
```

*## here we have three colors and we can set the value of the midpoint*

# The Olympic Games Dataset

This is a historical dataset on the modern Olympic Games, including all the Games from Athens 1896 to Rio 2016. I scraped this data from sports-reference in May 2018.

Note that the Winter and Summer Games were held in the same year up until 1992. After that, they staggered them such that Winter Games occur on a four year cycle starting with 1994, then Summer in 1996, then Winter in 1998, and so on. A common mistake people make when analyzing this data is to assume that the Summer and Winter Games have always been staggered.

**Content** The file `athlete_events.csv` contains 271116 rows and 15 columns. Each row corresponds to an individual athlete competing in an individual Olympic event (athlete-events). The columns are:

- ID - Unique number for each athlete
- Name - Athlete's name
- Sex - M or F
- Age - Integer
- Height - In centimeters
- Weight - In kilograms
- Team - Team name
- NOC - National Olympic Committee 3-letter code
- Games - Year and season
- Year - Integer
- Season - Summer or Winter
- City - Host city
- Sport - Sport
- Event - Event
- Medal - Gold, Silver, Bronze, or NA



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## Assignment #7

- Get the “Olympic Game Dataset” from Github
- Consider the athletes which were getting a medal in the Athletics Men’s 100 metres
- Do we see a trend in Age, Height, Weight over the years?
- Can you do the same for the BMI (body mass index)
- Do you see the same trend for Downhill Alpine Skiing?
- Do you see the same trend for a discipline of endurance like marathon?

## Grouping and summarising

- `group_by()`: this function can be used inside a pipe to group the samples on the bases of a set of discrete variables. Grouping can be removed from a tibble by using the `ungroup()` function
- `summarise()`: this function can be used apply some sort summary function (e.g. mean, median, sd, ...) on the grouped data frame. `summarise` can be used also to calculate multiple statistics

```
## single summarise  
summarise(mymean = mean(var), ## what function should be applid.  
          n = length(var)) ## another summary function
```

To summarize more than one columns grouping should be combined with `gather` ;-)



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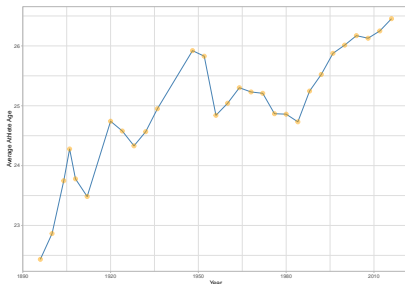


## Assignment #8

- Get the “Olympic Game Dataset”
- List the athletes who won more than 4 gold medals in at least one summer olympic games
- Save the list with their info in a file and load it in Excel

# Average Age in Athletics

```
athl %>%  
  filter(Sport == "Athletics") %>%  
  filter(Sex == "M") %>%  
  group_by(Year) %>%  
  summarise(avg_age = mean(Age, na.rm = TRUE)) %>%  
  ungroup() %>%  
  ggplot() +  
  geom_line(aes(x = Year, y = avg_age), col = "steelblue") +  
  geom_point(aes(x = Year, y = avg_age), col = "orange", alpha = 0.5, size = 3) +  
  ylab("Average Athlete Age") +  
  theme_light()
```



## Assignment #9

- Get the “Olympic Game Dataset”
- Make a plot showing the trend of the average BMI of the participants/medal winners for a set of running disciplines of increasing length (100m, 200m, 400m, 800m, 1500m, 5000m, 10000m, marathon)

Note: some helpful code hits are included in practical\_3

## Section 6

# Functions

# Functions

- Functions are the workhorse of all programming languages
- Almost everything we have been doing so far is actually performed by functions
- The packages are basically extending the language capabilities by adding new functions

## Why should one write a function?

- If I do several time the same operation a function saves me time
- If I do several time the same operation a function prevents me of making copy/paste errors

## Anatomy of a function

*## this is the anatomy of a function called pippo*

```
pippo <- function(inputs){  
  ## here I do something on the inputs  
  output <- something(input)  
  return(output)  
}
```

*## after the previous definition I can use pippo as*

```
a <- pippo(b)
```

# Notes

## Remember!

- it is wise to use meaningful names ;-) (not pippo)
- the function can have multiple inputs
- the function can output only one R object (if you want complex output you should wrap them into a list)
- the variable created inside the function are not living in the workspace. Their **scope** is limited.





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## Assignment #10

- Create a function which calculate the average value of a numeric vector
- Create a function which scales a vector to the interval  $[0,1]$ . So the minimum of the vector should be shifted to zero and the maximum scaled to one.

## *if* statements

*## If statements are often used condition the output of the  
## The if command in R looks like*

```
if (condition) {  
  # do this  
} else {  
  #do that  
}
```



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## Assignment #11

- Create a function which calculates the absolute value of a number
- Create a function which check if the length of a vector is even or odd

## Function arguments

As we have anticipated, functions can have multiple inputs (**arguments**) which can be used to tune the behavior of the function, adapting it to different use cases. Arguments have, in general, default values which are defined during the function definition

```
pippo <- function(a, b = 10, c = "ciao"){  
  ## b and c are have default values, If they are not explicitly  
  ## changed the function will work with them  
  ## here I do something on the inputs  
  output <- something(a,b,c)  
  return(output)  
}
```

```
pippo(10) ## a is set to 10, b and c keep their default values  
pippo(10, b = 9) ## a is 10, b is now 9, while c keeps "ciao"
```

## Assignment #12

- Create a function which calculates either the mean or the standard deviation of a vector. The choice should be performed by setting a specific argument in the function call
- Create a function which calculate the mean of a numeric vector excluding missing values.
- Use your function to calculate the mean inside a `summarise()` call in your analysis pipeline for the Assignment #9